

# Scalable real-time distributed DER control

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# **Project Objectives**

#### **AC OPF Theory**

Math foundation for convex relaxation of OPF

#### DER optimization algorithms

- Balanced mesh networks
- Unbalanced radial networks
- Centralized and distributed algorithms

#### Modeling

- SCE distribution systems, feeders & secondary circuits
- Implementation & demo
- Tech-2-market





# **Project Objectives**

#### Uniqueness

- Guaranteed optimality and convergence
- New framework for algorithm design

#### Challenges

- Mesh networks, unbalanced networks
- Distributed algorithms with guarantees (stab, perf)
- Numerical stability

#### Performance metrics

- Distributed algorithm for unbalanced radial network
  - size (demo'ed): 2,000 buses
  - time: 5 mins
  - optimality gap: 5%



Algorithms scalable to 10K nodes and beyond

- Convex relaxation of unbalanced network
- Distributed relaxation algorithms
- Distribution system modeling
- Implementation & demo





#### Convex relaxation for unbalanced network

- Theory
  - Chordal relaxation (exploits sparsity)
  - Branch flow model, bus injection model
- Algorithms
  - Extension of semidefinite algorithms to unbalanced radial networks
  - Centralized and decentralized algorithms
- Simulations
  - Centralized alg: SCE 2,000-bus, 3 mins, 0% gap
  - Distributed alg: IEEE 123-bus, 3 mins, 0% gap







# Simulation results (Aug 2014 review)

	Simulation performance	Target performance
#instances (4 week)	8,064	8,064
#instances solved (convergence) suboptimality gap (exactness)	100%	80% 5%
solution time (per instance)	2 min	3 mins

- Uses generalized BFM chordal relaxation using Rossi (~2000-bus) feeder
- Much more numerically stable than BIM
- Ran on 16 servers
- Exactness (ev ratios): 16.6M ratios (= 2064 lines/instance x 8064 instances)

#### Distributed relaxation algorithms

- Theory and algorithms: build on
  - Convex relaxation of OPF
  - Branch flow model
  - ADMM
- Simulations
  - Balanced radial network: 2,000 buses, 3 mins, 0% optimality gap
  - Unbalanced radial network: ~100 buses, <4 mins, 0% optimality gap</li>







# Computation time



Network size N	Diamete r D	Iterations	Total Time	Avg time T
2,065 buses	64 links	1,114	1,153 sec	0.56 sec
1,313	54	671	471	0.36
792	53	524	226	0.29
363	36	289	66	0.18
108	<b>1</b> 6	267	16	0.14

• Suboptimality gap : 0%

Compute time in distributed execution

#### **Scalability trend**

Regression:  $T = 9.8 \times 10^{-7} \,\text{N} + 8.6 \times 10^{-3} \,\text{D}$ 



# Comparison: ADMM-based algs



#### Huge speedup

- Recent distributed OPF algorithms (inc ours) are ADMM-based
- All these algorithms solve the ADMM subproblems in each update iteratively
- Ours solves them in closed form

per-bus computation time	x-update	z-update
Our algorithm	1.7 x 10 <sup>-4</sup> sec	5.1 x 10 <sup>-4</sup> sec
CVX	2 x 10 <sup>-1</sup> sec	3 x 10 <sup>-1</sup> sec
speedup	1,176x	588x

per-bus computation time: time to solve 1 sample ADMM iteration for Rossi circuit with 2,065 buses, divided by 2,065, for both algorithms

#### Distribution system modeling

- SCE systems
  - 6 feeders (4KV, 12KV)
  - ~15,000 buses
  - <10% error compared with substation measurements</li>

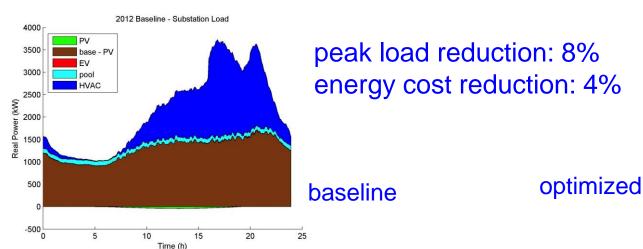


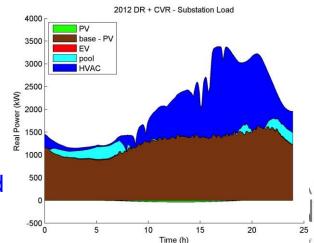




#### Implementation & demo

- SCE Rossi feeder
  - ~2,000 buses
  - DER: inverters, HVAC, EV, pool pumps
  - Unbalanced multiphase
  - 4-week simulations

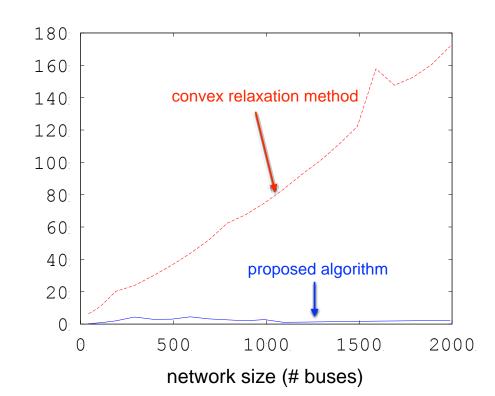




# Remaining tasks

#### Distributed OPF for unbalanced network

- SCE Rossi feeder: ~2,000 buses
- time: 5 mins
- optimality gap: 5%







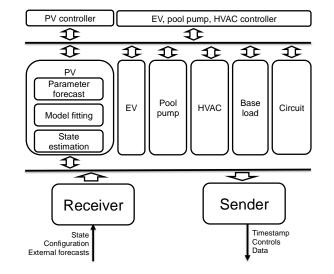
#### **Tech-to-market**

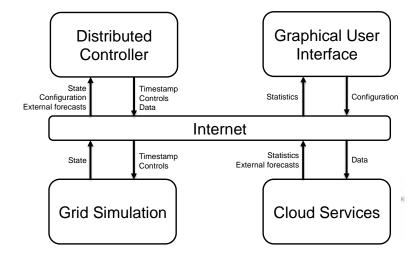
#### ▶ T2M objectives

Validation: market, technology

#### Key activities

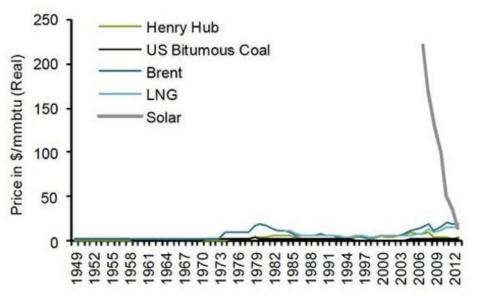
- IAB, Berkeley Haas C2M project
- Prototype
- Pilots, VC and strategic investments

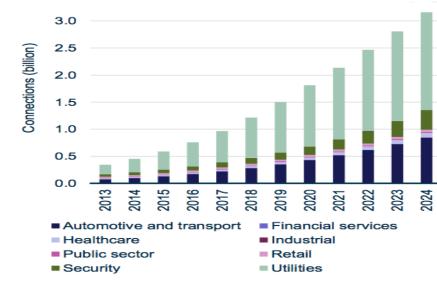


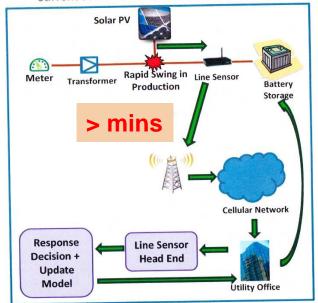


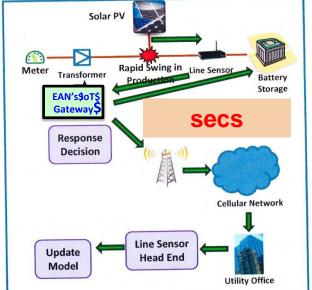


#### **Tech-to-market**













# Post ARPA-E goals

#### New R&D

- Builds on existing results for fast timescale dynamic control & optimization
- Scalable distributed real-time control with guaranteed stability and performance

#### Implementation & pilots

- Commercial grade software for DERMS
- Pilots with industry
- **▶** Tech-to-market





#### **Conclusions**

#### Most important contributions

- Math foundation for convex relaxation of OPF
- Relaxation algorithms: unbalanced radial, distributed
- Detailed feeder models
- Implementation & demo

#### Challenges

- Numerical instability, scalability
- Data for realistic and detailed models
- T2M: prototype, pilots





# Backup slides







$$u(t) = \underset{u}{\operatorname{argmin}} \operatorname{OPF}(u; \hat{x}(t))$$

estimate & learn

$$\hat{x} = \hat{f}(\hat{x}(t), u(t); e(t))$$

$$\hat{y} = \hat{g}(\hat{x}(t), u(t))$$

$$e(t) = y(t) - \hat{y}(t)$$

y(t)

u(t)

#### **GridLab-D simulator**

$$x = f(x(t), u(t))$$

$$y = g(x(t), u(t))$$

estimate state in fast timescale